Docket No.: 1454.1212

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE BOARD OF PATENT APPEALS AND INTERFERENCES

In re Patent Application of:

Christian ENSEL et al.

Application No.: 10/042,278 Group Art Unit: 2152

Filed: January 11, 2002 Examiner: Victor D. Lesniewski

For: SYSTEM FOR MONITORING TELECOMMUNICATION NETWORK AND TRAINING STATISTICAL ESTIMATOR

APPEAL BRIEF

Commissioner for Patents
PO Box 1450
Alexandria, VA 22313-1450

Sir:

In response to the Notification of Non-Compliant Appeal Brief mailed November 29, 2007, the following is submitted.

I. Real Party in Interest

The inventors Christian ENSEL and Volkmar STERZING assigned all rights in the subject application to SIEMENS AKTIENGESELLSCHAFT on January 18, 2002 according to the Assignment executed January 18, 2002 by Christian ENSEL and January 25, 2002 by Volkmar STERZING, and recorded at Reel 012580, Frame 0846 on February 14, 2002. Therefore, the real party in interest is SIEMENS AKTIENGESELLSCHAFT.

II. Related Appeals and Interferences

There are no related appeals or interferences known to Appellant, Appellant's legal representatives or the Assignee, SIEMENS AKTIENGESELLSCHAFT, which will directly affect or be directly affected by or have a bearing on the Board's decision in the pending appeal.

III. Status of Claims

Claims 12 and 15-26 are canceled and claims 1-11, 13, 14 and 27-29 are pending in the application. Claims 1-11, 13, 14 and 27-29 stand rejected under 35 U.S.C. § 103(a). The rejection of claims 1-11, 13, 14 and 27-29 is appealed.

IV. Status of Amendments

No Amendments were filed subsequent to the final Office Action.

V. Summary of Claimed Subject Matter

Independent Claim 1

Claim 1 is directed to a method of monitoring a telecommunications network that has a plurality of devices and services capable of communication, as described in page 4, lines 13-16, of the substitute specification.

The preamble of claim 1 recites a method for "computer-aided monitoring of a telecommunication network formed of devices capable of communication" (lines 1-2). An embodiment is shown in FIG. 4 and described in page 13, lines 11-12, and page 14, lines 13-19, of the substitute specification.

The body of claim 1 recites "determining training activity parameters, each describing activity of at least one of a corresponding device and a corresponding service" at lines 4-5. Examples of "determining training activity parameters" are described in page 12, lines 22-13. In addition, activity parameters are defined in page 5, lines 14-15. Examples of activity parameters are described in page 7, lines 12-21.

Claim 1 also recites "determining possible dependences between devices and services from the training activity parameters" at lines 6-7. Examples of determining possible dependences are described in page 7, lines 8-16.

Claim 1 further recites "determining from the possible dependences a normal range of dependence for at least some of the devices and services in essentially undisturbed states to train a neural network as a statistical estimator" at lines 8-11. An example of "determining from the possible dependences a normal range of dependence" is described in page 5, lines 14-15. One embodiment of "train[ing] a neural network as a statistical estimator" is described in page 8, lines 9-11. Examples of the "statistical estimator" are discussed in page 8, lines 22-24.

Lines 12-13 of claim 1 recite "determining current activity parameters, each describing activity of at least one of a corresponding device and a corresponding service". An example of "determining current activity parameters" is discussed in page 14, lines 4-6.

Lines 14-15 of claim 1 recite "comparing the current activity parameters by the statistical estimator with the normal range of dependence". An example of such a comparison is discussed in page 14, lines 13-14.

Finally, claim 1 recites "determining from said comparing whether at least one of the devices and services in the telecommunication network has a communication performance different from the normal range of dependence in accordance with a predetermined criterion" in lines 16-18. An example is discussed in page 14, lines 13-19.

Independent Claim 27

Claim 27 is directed to a device for monitoring a telecommunications network that has a plurality of devices and services capable of communication, as described in page 4, lines 13-16, and page 9, lines 14-17, of the substitute specification.

The preamble of claim 27 recites a "device for computer-aided monitoring of a telecommunication network formed of devices capable of communication" (lines 1-2). An embodiment is described in page 9, lines 14-17, page 13, lines 11-12, and page 14, lines 13-19, of the substitute specification.

The body of claim 27 recites "at least one processor to determine training activity parameters, each describing activity of at least one of a corresponding device and a corresponding service" at lines 3-4. As noted in page 9, lines 14-17, of the substitute specification, the application relates to both hardware and software. One skilled in the art would understand that the devices discussed in the specification may use more than one processor, because devices in a telecommunications network frequently use multiple processors. Furthermore, examples of determining training activity parameters are described in page 12, lines 22-23. Activity parameters are defined in page 5, lines 14-15 and examples of activity parameters are described in page 7, lines 12-21.

Claim 27 also recites "to determine possible dependences between devices and services from the training activity parameters" at lines 4-5. An examples of determining possible dependences are described in page 7, lines 8-16. One example is shown in FIG. 3 and described in page 13, lines 16-20, of the substitute specification.

Claim 27 further recites "to determine from the possible dependences a normal range of dependence for at least some of the devices and services in essentially undisturbed states to train a neural network as a statistical estimator" at lines 5-7. An example of "determin[ing] from the possible dependences a normal range of dependence" is described in page 5, lines 14-15. One embodiment of "train[ing] a neural network as a statistical estimator" is described in page 8, lines 9-11. Examples of the "statistical estimator" are discussed in page 8, lines 22-24.

Lines 8-9 of claim 27 recite "to determine current activity parameters, each describing activity of at least one of a corresponding device and a corresponding service". An example of "determin[ing] current activity parameters" is discussed in page 14, lines 4-6.

Lines 9-10 of claim 27 recites "to compare the current activity parameters by the statistical estimator with the normal range of dependence". An example of such a comparison is discussed in page 14, lines 13-14.

Finally, claim 27 recites "to determine from said comparing whether at least one of the devices and services in the telecommunication network has a communication performance different from the normal range of dependence in accordance with a predetermined criterion" in lines 10-13. An example is discussed in page 14, lines 13-19.

Independent Claim 28

Claim 28 is directed to a computer-readable storage medium storing at least one computer program monitoring a telecommunications network that has a plurality of devices and services capable of communication, as described in page 4, lines 13-16, and page 9, lines 14-15, of the substitute specification.

The preamble of claim 28 recites

> at least one computer-readable storage medium storing at least one computer program for computer-aided monitoring of a telecommunication network formed of devices capable of communication, to control a processor to perform a method

(lines 1-3). An example of the method stored on the computer-readable storage medium is shown in FIG. 4 and described in page 9, lines 14-15, page 13, lines 11-12, and page 14, lines 13-19, of the substitute specification.

The body of claim 28 recites "determining training activity parameters, each describing activity of at least one of a corresponding device and a corresponding service" at lines 5-6. Examples of "determining training activity parameters" are described in page 12, lines 22-23. In

addition, activity parameters are defined in page 5, lines 14-15. Examples of activity parameters are described in page 7, lines 12-21.

Claim 28 also recites "determining possible dependences between devices and services from the training activity parameters" at lines 7-8. Examples of determining possible dependences are described in page 7, lines 8-16. One example is described in page 13, lines 16-20, of the substitute specification.

Claim 28 further recites "determining from the possible dependences a normal range of dependence for at least some of the devices and services in essentially undisturbed states to train a neural network as a statistical estimator" at lines 9-11. An example of "determining from the possible dependences a normal range of dependence" is described in page 5, lines 14-15. One embodiment of "train[ing] a neural network as a statistical estimator" is described in page 8, lines 9-11. Examples of the "statistical estimator" are discussed in page 8, lines 22-24.

Lines 12-13 of claim 28 recite "determining current activity parameters, each describing activity of at least one of a corresponding device and a corresponding service". An example of "determining current activity parameters" is discussed in page 14, lines 4-6.

Lines 13-14 of claim 28 recite "comparing the current activity parameters by the statistical estimator with the normal range of dependence". An example of such a comparison is discussed in page 14, lines 13-14.

Finally, claim 28 recites "determining from said comparing whether at least one of the devices and services in the telecommunication network has a communication performance different from the normal range of dependence in accordance with a predetermined criterion" in lines 15-17. An example is discussed in page 14, lines 13-19.

Independent Claim 29

Claim 29 is directed to a computer-readable storage medium storing at least one computer program monitoring a telecommunications network that has a plurality of devices and services capable of communication, as described in page 4, lines 13-16, and page 9, lines 14-15, of the substitute specification.

The preamble of claim 29 recites

> [a]t least one computer-readable storage medium storing at least one computer program for computer-aided training of a neural network as a statistical estimator for administering a telecommunication network formed of devices capable of communication, to control a processor to perform a method

(lines 1-4). An example of the method stored on the computer-readable storage medium is shown in FIG. 4 and described in page 9, lines 14-15, page 13, lines 11-12, and page 14, lines 13-19, of the substitute specification.

The body of claim 29 recites "determining training activity parameters, each describing activity of at least one of a corresponding device and a corresponding service" at lines 5-6. Examples of "determining training activity parameters" are described in page 12, lines 22-23, and include a back-propagation training method. In addition, activity parameters are defined in page 5, lines 14-15. Examples of activity parameters are described in page 7, lines 12-21.

Claim 29 also recites "determining possible dependences between the devices and services from the training activity parameters" at lines 7-8. Examples of determining possible dependences are described in page 7, lines 8-16. One example is shown in FIG. 3 and described in page 13, lines 16-20, of the substitute specification.

Claim 29 further recites

> determining from the possible dependences a normal range of dependence for at least some of the devices and services in essentially undisturbed states to train the statistical estimator for determining current activity parameters, each describing activity of at least one of a corresponding device and a corresponding service and comparing the current activity parameters with the normal range of dependence

(lines 9-13). An example of "determining from the possible dependences a normal range of dependence" is described in page 5, lines 14-15. One embodiment of "training a neural network as a statistical estimator" is described in page 8, lines 9-11. Examples of the "statistical estimator" are discussed in page 8, lines 22-24. An example of "determining current activity parameters" is discussed in page 14, lines 4-6. An example of "comparing the current activity parameters with the normal range of dependence" is discussed in page 14, lines 13-14.

VI. Grounds of Rejection to be Reviewed on Appeal

In the final Office Action mailed April 3, 2007, claims 1-11, 13, 14, and 27-29 were rejected under 35 USC § 103(a) as unpatentable over Waclawsky et al. (U.S. Patent No. 5,974,457) in view of Nuansri et al. ("An Application of Neural Network and Rule-Based System for Network Management: Application Level Problems").

VII. Argument

Numbered paragraph 5, on pages 2 of the final Office Action, states that claims "1-11, 13, 14, and 27-29 remain rejected under 35 USC § 103(a)" as unpatentable over Waclawsky et

al. (U.S. Patent Number 5,974,457) in view of Nuansri et al. ("An Application of Neural Network and Rule-Based System for Network Management: Application Level Problems"). Nothing further is stated in the final Office Action regarding the rejection under 35 U.S.C. § 103(a). Therefore, in the argument that follows, the Applicants assume the Examiner has maintained the rejection of claims 1-11, 13, 14, and 27-29 as it appeared in the Office Action mailed October 21, 2006.

Discussion of the prior art and one skilled in the art.

Any discussion of "neural networks", "rule-based systems" and "expert systems", as described in the prior art of record, invariably involves a discussion of Artificial Intelligence. As described by "Artificial Intelligence: An Overview" (Honavar V., Principles of Artificial Intelligence, Com S 572, Fall 2006, Iowa State University, last revised August 21, 2006, hereinafter Honavar '06), "[t]he term Artificial Intelligence refers to the enterprise of understanding and building intelligent systems" (see Exhibit 1). Honavar '06 then goes on to list milestones in the field and gives a brief discussion of "neural networks" (page 6, 11th bullet point), "rule-based systems" (page, 6, 2nd bullet point) and "expert systems" (page 7, 7th bullet point). Although Honavar '06 was last revised in 2006, the definition provided by Honavar '06 and the subsequent discussion of Artificial Intelligence demonstrates that terms "neural networks", "rule-based systems" and "expert systems" as used in the prior art pertain to Artificial Intelligence.

While both "rule-based systems" and "expert systems" (often referred together as "symbolic Artificial Intelligence") and "neural networks" relate to the field of Artificial Intelligence, those skilled in the art have long recognized that there is a difference in the two approaches to the problem of Artificial Intelligence. For example, in "Symbolic Artificial Intelligence and Numeric Artificial Neural Networks: Toward a Resolution of the Dichotomy" (Honavar V., Computational Architectures Integrating Symbolic and Neural Processes. Sun, R. & Bookman, L. (Ed.) New York, NY: Kluwer, 1994, hereinafter Honavar '94, see Exhibit 2), Honavar '94 states that

> [i]t is often suggested that two major approaches have emerged – symbolic artificial intelligence (SAI) and (numeric) artificial intelligence (NANN or connectionist networks) and some (Norman 1986, Schneider, 1987) have even suggested that they are fundamentally and irreconcilably different

(page 2, lines 1-5). While Honavar '94 later states "[t]his chapter argues that the dichotomy between SAI and NANN is more perceived than real" (page 2, lines19-20), Honavar '94 demonstrates that a person of ordinary skill in the art of Artificial Intelligence understands that there is an articulable difference between "rule-based systems" and "neural networks".

Of the prior art relied on in the Office Action mailed October 21, 2006, Waclawsky et al. disclosed a only a rule-based system. Rule-based systems consist of a number of manually defined rules representing what the rule-based system's designers consider to be an expert in the field's knowledge base. Rule-based systems are also referred to as "expert systems" or "knowledge-based systems". Another way of describing how a rule-based system is created and operates is: "[k]nowledge engineering is a field within artificial intelligence that develops knowledge-based systems. ... A major form of knowledge-based system[s] is an expert system, one designed to emulate the reasoning processes of an expert practitioner" (*see* "www.epistemics.co.uk/Notes/61-0-0.htm", accessed August 29, 2007; as Exhibit 3; *see also* Honavar '06, page, 6, 2nd bullet point). Waclawsky et al. describes the embodiment of this process used in FIG. 1A-1 as "[t]he expert system analysis module 160 contains the rule based criteria modules 150, 150' and 150["], which contain rules which will characterize the classes of traffic on the network being monitored" in column 4, lines 43-46.

Nuansri et al. disclosed a hybrid system that puts a neural network system in a serial connection with a rule-based system. The two systems are discrete parts of the overall system, as shown in Fig. 13 on page 480. Specifically, in Nuansri et al., the neural network system is labeled BRAINNE in Fig. 13 and the rule-based system is labeled NEXPERT according to section 5. Furthermore, as further described in section 5, "BRAINNE is used as an automated knowledge acquisition tool that allows us to extract ... DNS faults (errors) and their causes while the NEXPERT system is later used as a rule-based expert system for the analysis and diagnosis part." Thus, the system described in Nuansri et al. used a neural network system as a pre-processor to a rule-based system.

Patentable distinctions between the claims and prior art of record

Claim 1 recites "determining from the possible dependences a normal range of dependence for at least some of the devices and services essentially undisturbed states to train a neural network as a statistical estimator" (claim 1, lines 8-10). The first two lines of page 4 in the Office Action mailed October 21, 2006 alleged that Nuansri et al. "train[ed] a neural network as a statistical estimator to effectuate network monitoring and diagnosing." The Applicant's disagree with this assessment of Nuansri et al.

One shortcoming of the October 21, 2006 Office Action's assessment regarding Nuansri et al. is the failure to cite where Nuansri et al. disclosed a *statistical estimator*. Nothing can be found in Nuansri et al. that teaches any statistical methods used to act as a statistical estimator. What has been found, in sections 5.1, describe the training of BRAINNE by reading a log file to

retrieve error messages as one component and "extracting knowledge from experience and human experts and from forcing faults on a name server" to retrieve possible causes of the error messages as the second component. Since the training of BRAINNE uses log files to retrieve error messages, it is submitted that Nuansri et al. does not describe anything "determining from the possible dependences a normal range of dependence for at least some of the devices and services essentially undisturbed states" as recited in claim 1 at lines 8-9. Moreover, a statistical estimator, such as the neural network recited in claim 1, does not require an expert to create rules. Rather, the statistical estimator represents the required knowledge after training in implicit form. Thus, by relying on a rule based system, Waclawsky et al. teaches away from a statistical estimator training system.

Additionally, as discussed above, Nuansri et al. does not describe the neural network system as a monitoring or diagnosing system, but rather as a pre-processor. This is evident by the structure shown in Fig. 13, where the neural network system (BRAINNE) outputs to the rule-based system (NEXPERT KB) in the sub-graph labeled "Learning Process" and the rule-based system (NEXPERT interface) received its input from a log file in the sub-graph labeled "Monitoring and diagnosing Process" in Fig. 13.

In the final Office Action mailed April 3, 2007, the Examiner argues that Waclawsky et al. "has been cited in the rejection for detail in determining a normal range of dependence" (numbered paragraph 8, line 4). It is not clear where the Examiner has previously analyzed and demonstrated that Waclawsky et al. teaches or suggests "determining a normal range of dependence" and nothing has been found in the record supporting this statement in the final Office Action. Instead, the October 21, 2006 Office Action merely cites both Waclawsky et al. (column 4, line 50 through column 5, line 4) and Nuansri et al. (page 478, first paragraph) as teaching or suggesting "determining from the possible dependences a normal range of dependence for at least some of the devices and services in essentially undisturbed states to train a neural network as a statistical estimator" (last four lines of page 4 of the October 26, 2007 Office Action).

Waclawsky et al. states "[t]he comparison is performed by the rules contained in the rule based criteria modules 150 ... standards can be predetermined, predefined standards such as *average* utilization for particular types of traffic such as batch traffic, interactive traffic, voice traffic or video traffic" in column 4, lines 60-63, emphasis added. Thus, the "standard" as taught by Waclawsky et al. is a scalar value, specifically an "average" value. Waclawsky et al. then goes on to state "[a]nother important type of standard is the benchmark data set which is the accumulated history of behavior of traffic on the network" at column 4, lines 63-65. Waclawsky

et al. does not further describe how the "benchmark data set" could be used as a "normal *range* of dependence" as recited in the claims (*e.g.* claim 1 at line 8, emphasis added). Instead, Waclawsky et al. simply states that the "benchmark data sets ... progressively accumulate a more accurate representation of the expected behavior for the network and that standard can be substituted for the predetermined standard used by the rules in the rule based criteria modules" in column 4, line 66 to column 5, line 4). Given what has been quoted above from Waclawsky et al., one of ordinary skill in the art would understand Waclawsky et al. to teach or suggest using "benchmark data sets" to calculate an average and using the calculated average of the "benchmark data sets" as the standard instead of the "average utilization for particular types of traffic such as batch traffic, interactive traffic, voice traffic or video traffic" as the standard.

For the foregoing reasons, it is submitted that the rejections of claims 1-11, 13, 14, and 27-29 under 35 USC § 103(a) as unpatentable over Waclawsky et al. in view of Nuansri et al. was improper because nothing on record has been shown to teach or suggest a "statistical estimator" or a "normal range of dependence" as quoted above from the claims. The Board is respectfully requested to reverse the Examiner's final rejection.

Improper Combination

Furthermore, Applicants respectfully submit that the combination of Waclawsky et al. and Nuansri et al. is improper. In the October 21, 2006 Office Action, Nuansri et al. is relied upon as disclosing the statistical estimator requirements of the claim as recited in the third operation of claim 1. However, all other operations recited in the claimed method are allegedly taught or suggested by Waclawsky et al. The references Nuansri et al. and Waclawsky et al. are disparate teachings raising the question of why a person skilled in the art would even consider these references for combination, a question the Board must answer[1] since the Examiner did not. The statements in the October 21, 2006 Office Action that Nuansri et al. is "an analogous art"[2] and that "it would have been obvious to a person skilled in the art at the time of the applicant's invention to modify ..."[3] are conclusory statements that do not constitute "sufficient factual findings."[4] Applicants respectfully traversed the obviousness rejection based on

[1] See *In re Lee*, 277 F3d 1338, 61 USPQ2d 1430, 1434 (Fed. Cir. 2002), "the Board must explain the reasons one of ordinary skill in the art would have been motivated to select the references."

[2] See item 9 of the Office Action, lines 2-3.

[3] See item 10 of the Office Action, lines 7-8.

[4] MPEP 2144.08 III states that "[e]xplicit findings on motivation or suggestion to select the claimed invention should also be articulated in order to support a 35 U.S.C. § 103 ground of rejection. . . Conclusory statements of similarity or motivation, without any articulated rational or evidentiary support, do

Waclawsky et al. and Nuansri et al. because there is insufficient evidence for a motivation to use the method of Nuansri et al. in the system described by Waclawsky et al. in the Response filed January 31, 2007. While the required evidence of motivation to combine need not come from the applied references themselves, the evidence must come from *somewhere* within the record.[5] In this case, the record fails to support the proposed combination.

Dependent claims 2-14 depend from claim 1. Independent claims 27-29 recite statistical estimator limitations in a manner similar to claim 1. Thus, claims 2-14 and 27-29 distinguish over the applied art for the reasons discussed in regard to claim 1.

Summary of Arguments

For the reasons set forth above and in the Request for Reconsideration filed January 31, 2007, it is respectfully submitted that claims 1-11, 13, 14, and 27-29 patentably distinguish over the prior art. Thus, it is respectfully submitted that the Examiner's final rejection of the claims is without support and, therefore, erroneous. Accordingly, the Board of Patent Appeals and Interferences is respectfully urged to so find and to reverse the Examiner's final rejection.

Please charge the required fee in the amount of $500.00 to our Deposit Account No. 19-3935. If any additional fees are required for this Appeal Brief, please charge same to our Deposit Account No. 19-3935.

Respectfully submitted,

STAAS & HALSEY LLP

Date: January 29, 2008

By: /David E. Moore/
David E. Moore
Registration No. 59,047

1201 New York Avenue, NW, Suite 700
Washington, D.C. 20005
Telephone: (202) 434-1500
Facsimile: (202) 434-1501

---

not constitute sufficient factual findings."

[5] *In re Lee*, 277 F.3d 1338, 1343-4, 61 USPQ2d 1430 (Fed. Cir. 2002) ("The factual inquiry whether to combine references ... must be based on objective evidence of record. ... [The] factual question of motivation ... cannot be resolved on subjective belief and unknown authority. ... Thus, the Board must not only assure that the requisite findings are made, based on evidence of record, but must also explain the reasoning by which the findings are deemed to support the agency's conclusion").

VIII. Claims Appendix

1. A method for computer-aided monitoring of a telecommunication network formed of devices capable of communication, said method comprising:

determining training activity parameters, each describing activity of at least one of a corresponding device and a corresponding service;

determining possible dependences between devices and services from the training activity parameters;

determining from the possible dependences a normal range of dependence for at least some of the devices and services in essentially undisturbed states to train a neural network as a statistical estimator;

determining current activity parameters, each describing activity of at least one of a corresponding device and a corresponding service;

comparing the current activity parameters by the statistical estimator with the normal range of dependence; and

determining from said comparing whether at least one of the devices and services in the telecommunication network has a communication performance different from the normal range of dependence in accordance with a predetermined criterion.

2. The method as claimed in claim 1, wherein at least some of the devices are constructed as terminals capable of communication.

3. The method as claimed in claim 1, wherein the training activity parameters are determined within a predetermined time interval.

4. The method as claimed in claim 1,

wherein said determining of each training activity parameter is performed by the corresponding device, and

wherein said method further comprises transmitting the training activity parameters to an administration unit which performs said comparing and determining based on said comparing.

5. The method as claimed in claim 1, wherein said determining of each training activity parameter is performed by a training activity parameter determining unit separate from the corresponding device.

6. The method as claimed in claim 1, further comprising determining communication-dependent dependences between at least some of the devices and services.

7. The method as claimed in claim 1, further comprising determining possible directional dependences with regard to directions of communication between at least some of the devices and services.

8. The method as claimed in claim 1,

further comprising determining data of at least some of the devices and services, and wherein said determining of the training activity parameters is based on the data.

9. The method as claimed in claim 1, wherein said determining of the training activity parameters uses all possible pairs of the devices and pairs of services.

10. The method as claimed in claim 9, further comprising:

storing the training activity parameters determined from the pairs of devices in a matrix; and

determining the normal range of dependence from a structure of the matrix.

11. The method as claimed in claim 1, wherein at least one of the following parameters is determined as one of the training activity parameters

data packets sent or received by the at least one of a corresponding device and a corresponding service,

processor utilization of the corresponding device,

a number of predetermined system function calls, and

existence of at least one of predetermined processes and predetermined computer programs.

13. (Original) The method as claimed in claim 1, further comprising generating an alarm signal when at least one device in the telecommunication network differs from the normal range of dependence in accordance with the predetermined criterion.

14. (Original) The method as claimed in claim 1, further comprising at least one of

determining a disturbance of one of the devices in the telecommunication network;

determining an unauthorized attempt to access one of the devices; and determining an unauthorized access attempt by one of the devices.

27. A device for computer-aided monitoring of a telecommunication network formed of devices capable of communication, comprising:

at least one processor to determine training activity parameters, each describing activity of at least one of a corresponding device and a corresponding service, to determine possible dependences between devices and services from the training activity parameters, to determine from the possible dependences a normal range of dependence for at least some of the devices and services in essentially undisturbed states to train a neural network as a statistical estimator, to determine current activity parameters, each describing activity of at least one of a corresponding device and a corresponding service, to compare the current activity parameters by the statistical estimator with the normal range of dependence, and to determine from said comparing whether at least one of the devices and services in the telecommunication network has a communication performance different from the normal range of dependence in accordance with a predetermined criterion.

28. At least one computer-readable storage medium storing at least one computer program for computer-aided monitoring of a telecommunication network formed of devices capable of communication, to control a processor to perform a method comprising:

determining training activity parameters, each describing activity of at least one of a corresponding device and a corresponding service;

determining possible dependences between devices and services from the training activity parameters;

determining from the possible dependences a normal range of dependence for at least some of the devices and services in essentially undisturbed states to train a neural network as a statistical estimator;

determining current activity parameters, each describing activity of at least one of a corresponding device and a corresponding service; comparing the current activity parameters by the statistical estimator with the normal range of dependence; and

determining from said comparing whether at least one of the devices and services in the telecommunication network has a communication performance different from the normal range of dependence in accordance with a predetermined criterion.

29. At least one computer-readable storage medium storing at least one computer program for computer-aided training of a neural network as a statistical estimator for administering a telecommunication network formed of devices capable of communication, to control a processor to perform a method comprising:

determining training activity parameters, each describing activity of at least one of a corresponding device and a corresponding service;

determining possible dependences between the devices and services from the training activity parameters; and

determining from the possible dependences a normal range of dependence for at least some of the devices and services in essentially undisturbed states to train the statistical estimator for determining current activity parameters, each describing activity of at least one of a corresponding device and a corresponding service and comparing the current activity parameters with the normal range of dependence.

IX. Evidence Appendix

Exhibit 1: Honavar V., Principles of Artificial Intelligence, Com S 572, Fall 2006, Iowa State University

Exhibit 2: Honavar V., Computational Architectures Integrating Symbolic and Neural Processes. Sun, R. & Bookman, L. (Ed.) New York, NY: Kluwer, 1994

Exhibit 3: www.epistemics.co.uk/Notes/61-0-0.htm", accessed August 29, 2007

X. Related Proceedings Appendix

(None)

EXHIBIT 1

Artificial Intelligence: An Overview *

Vasant Honavar
Artificial Intelligence Research Laboratory
Center for Computational Intelligence, Learning, and Discovery
Department of Computer Science
226 Atanasoff Hall
Iowa State University
Ames, Iowa 50011

Last revised: August 21, 2006

Abstract

This chapter reviews common-sense definitions of intelligence; motivates the research in artificial intelligence (AI) that is aimed at design and analysis of programs and computers that model minds/brains; lays out the fundamental guiding hypothesis of AI; reviews the historical development of AI as a scientific and engineering discipline; explores the relationship of AI to other disciplines; and presents an overview of the scope, problems, and major areas of AI. Hopefully this discussion will not only provide a useful context for the technical material that follows but also convey a sense of what scientists, engineers, mathematicians, and philosophers who have been drawn to the field find exciting about AI. The views presented here are necessarily biased by the author's own research. The readers are encouraged to explore alternative views and perspectives on this subject.

1 What is Intelligence?

Try precisely defining intelligence. It is next to impossible. Despite the wide use (and misuse) of terms such as *intelligent systems*, there is no widely agreed-upon scientific definition of *intelligence*. It is therefore useful to think of intelligence in terms of an open collection of attributes. What follows is a wish-list of general characteristics of intelligence that contemporary researchers in AI and cognitive science are trying to understand and replicate. It is safe to say that no existing AI system comes anywhere close to exhibiting intelligence as characterized here except perhaps in extremely narrowly restricted domains (e.g., organic chemistry, medical diagnosis, information retrieval, network routing, military situation assessment, financial planning):

- **Perception** — manipulation, integration, and interpretation of data provided by sensors (in the context of the internal state of the system — including purposeful, goal-directed, active perception).

- **Action** — coordination, control, and use of effectors to accomplish a variety of tasks including exploration and manipulation of the environment, including design and construction of tools towards this end.

- **Reasoning** — deductive (logical) inference, inductive inference, analogical inference — including reasoning in the face of uncertainty and incomplete information, hypothetical reasoning, justification and explanation of inferences, evaluation of explanations, adapting explanations in the light of falsified assumptions or changing world states.

*Principles of Artificial Intelligence, Com S 572, Fall 2006, Iowa State University ©Vasant Honavar, 1992-2006

- **Adaptation and Learning** — adapting behaviour to better cope with changing environmental demands, discovery of regularities, explanation of observations in terms of known facts and hypotheses, construction of task-specific internal representations of the environment, discovery of procedures, learning to differentiate despite similarities and generalize despite differences, learning to describe specific domains in terms of abstract theories and concepts, learning to use, adapt, and extend language, learning to reason, plan, and act.

- **Communication** — with other intelligent agents including humans using signals, signs, icons, symbols, sound, pictures, touch, language and other communication media — including communication of goals, desires, beliefs, narratives of real and imaginary episodes, explanation of actions and events.

- **Planning and goal-directed problem-solving** — Formulation of plans — sequences or agenda of actions to accomplish externally or internally determined goals, evaluating and choosing among alternative plans, adapting plans in the face of unexpected changes in the environment, explaining and justifying plans, modifying old plans to fit new tasks, handling complexity by abstraction and simplification.

- **Autonomy** — Setting of goals, deciding on the appropriate course of actions to take in order to accomplish the goals or directives (without explicit instructions from another entity), executing the actions to satisfy the goals, adapting the actions and/or goals as necessary to deal with any unforeseen circumstances (to the extent permitted by the agent's physical capabilities and the environmental constraints).

- **Creativity** — exploration, modification, and extension of domains (e.g., language, mathematics, music) by manipulation of domain-specific constraints, or by other means.

- **Reflection and awareness** — of internal processes (e.g., reasoning, goals, etc.) of self as well as other agents.

- **Aesthetics** — articulation and use of aesthetic principles.

- **Organization** — into social groups based on shared objectives, development of shared conventions to facilitate orderly interaction, culture.

Most people would probably agree that the hallmark of intelligence is almost certainly not simply the ability to display some or all of the listed attributes but doing so on a broad and open-ended (not precisely pre-specified) set of domains and under a broad range of (a-priori unknown, possibly context-dependent and domain-specific) constraints (e.g., time allowed, tools available, accuracy desired). It is also clear that different systems — be they natural or artificial — can display different subsets of the attributes of intelligence to differing degrees.

2 What is Artificial Intelligence (AI)?

The attempt to understand intelligence entails building theories and models of (appropriately embodied) brains and minds, both natural as well as artificial. From the earliest writings of India and Greece, this has been a central problem in philosophy. The advent of the digital computer in the 1950's made this a central concern of computer scientists as well. The parallel development of the theory of computation (by John von Neumann, Alan Turing, Emil Post, Alonzo Church, Stephen Kleene, Markov and others) provided a new set of tools with which to approach this problem — through analysis, design, and evaluation of computers and programs that exhibit aspects of intelligent behavior — such as the ability to recognize and classify patterns; to reason from premises to logical conclusions; and to learn from experience.

The term *Artificial Intelligence* refers to the the enterprise of understanding and building intelligent systems. AI folklore credits John McCarthy (who incidentally, made several major contributions to AI and Computer Science in their infancy — by designing the programming language LISP and the first time-sharing operating system) with inventing the term during the workshop at Dartmouth in 1956 where the field took on its modern incarnation.

Here are some descriptions of AI:

- **Descartes** (1556–1650) discounts sensory experience as untrustworthy and justifies his own existence in terms of thought: *Cogito ergo sum* (I think, therefore I am) and with other contemporary thinkers, establishes the notion that the structure of ideas about the world are not necessarily the same as the structure of their subject matter, an idea which underlies much of the methodology of AI, epistemology, psychology, mathematics, and modern literature.
- **Hobbs** (1650) proposes that thinking is a rule-based computational process analogous to arithmetic.
- **Leibnitz** (1646-1716) seeks a general method in which all truths will be reduced to a kind of calculation.
- **Boole** (1815-1864) puts forth his study of logic and probability as an investigation into the laws of thought.
- **Russell, Frege, Tarski** (1910-1950) formalize logic and reduce large portions of mathematics to logic; Russell writes an influential book *Principia Mathematica.* Tarski introduces the theory of reference for relating objects in a logic to objects in the world, laying the foundations of formal semantics.
- **Hilbert** (1862-1943) presents the decision problem . Is there an effective procedure for determining whether or not a given theorem logically follows from a given set of axioms?
- **Godel** (1906-1978) shows the existence of an effective procedure to prove any theorem in Frege's logic and proves the incompleteness theorem
- **Turing** (1912-1954) invents the Turing Machine to formalize the notion of an effective procedure
- **Turing, Church, Kleene, Post** (1930-50) Turing and Church put forth the Church-Turing thesis that Turing machines are universal computers. Kleene and Post propose other Turing-equivalent models of computation
- Several special purpose analog and digital computers are built (including the Atanasoff-Berry Computer)
- **Chomsky** (1956) develops the Chomsky hierarchy of languages formalize the common-sense notion of computation in terms of effective procedures and universal computers.
- **Rashevsky, McCulloch, Ashby, Rosenblatt** (1930-60) — work on early neural network models.
- **Von Neumann, McCulloch** (1940-1956), investigate the relationship between the brain and the computer
- **Von Neumann and Morgenstern** (1946) develop a formal framework for rational decision making under uncertainty
- **Shannon** (1948) develops information theory, laying the foundations of coding and communication
- **von Neumann (1956)** works out a detailed design for a stored-program digital computer
- **Wiener, Lyapunov (1956)** develop the science of cybernetics to study control and communication in humans and machines.
- **McCarthy, Minsky, Newell, Selfridge, Simon, Turing, Uhr, et al.** (1956) establish AI in a workshop organized at Dartmouth College at the initiative of John McCarthy.
- Several digital computers are constructed and universal languages for programming them are developed e.g., Lisp, Snobol, Fortran.
- **Wittgenstein** (1950) challenges many of the underlying assumptions of the rationalist tradition, including the foundations of language, science, and knowledge itself; and proposes that the meaning of an utterance depends on being situated in a human, cultural context (e.g., the meaning of the word "chair" to me is dependent on my having a physical body that can take on a sitting posture and the cultural convention for using chairs).

- **Dantzig and Edmunds** (1960-62) introduce reduction, a general transformation from one class of problems to another

- **Cobham and Edmunds** (1964-65) introduce polynomial and exponential complexity

- **Cook and Karp** (1971-72) develop the theory of NP-completeness which helps recognize problems that are intractable

- **Cerf** (1974) invents the Internet

- **Husserl, Heidegger** (1960-1975) articulate the view that abstractions must be *rooted* or *grounded* in the concrete *lavensvelt* or *life-world* i.e., the rationalist model of Aristotle is very much secondary to the concrete world that supported it; in the existentialist/phenomenological view, intelligence is not knowing what is *true*, but knowing how to cope with a world that is constantly changing.

- 1960-1970 — untempered optimism fueled by early success on some problems thought to be hard (e.g., theorem proving) is tempered by slow progress on many problems thought to be easy (e.g., visual pattern recognition); much of the AI work is based in the rationalist/logical tradition; the field is fragmented into sub-areas focused on problem-solving, knowledge representation and inference, vision, planning, language processing, learning, etc.

- 1970-mid 1980s — investigation of knowledge representation and reasoning leads to many practical tools such as expert systems; the difficulty task of *knowledge engineering* draws attention to the need for systems capable of learning from experience and interaction with the world

- Internet is rolled out in 1984

- Mid 1980s-1990 — some of the failures of rationalist/logical approaches to AI lead to renewed interest in biologically inspired neural network and evolutionary models which lead to modest successes on some problems (e.g., pattern recognition) prompting a few to prematurely proclaim the death of "good old fashioned AI". Some propose alternative approaches (in the Heideggerian tradition) while others discover (and rediscover) the limitations of the alternatives being proposed.

- Mid 1980s-mid 1990s — progress in algorithmic models of learning begins to offer promising and practical alternatives to knowledge engineering and AI technologies begin to be used in critical components of large software systems; The most successful approaches incorporate the elements of both the rationalist/logical/symbolic tradition and the existential/phenomenological/non-symbolic tradition; proposals for reconciling the two approaches begin to appear; maturing of the several subfields of AI such as vision, language processing, knowledge representation, planning, etc. leads to insights on the capabilities as well as limitations of the techniques that were developed and redirects attention on the problem of building intelligent agents as opposed to subsystems and this further fuels synthesis of hybrid models.

- **Berners-Lee** (1989-91) invents the world wide web

- Mid 1990s-present — AI technologies continue to find applications in adaptive information retrieval, data mining and knowledge discovery from databases, customizable software systems, smart devices (e.g., homes, automobiles), agile manufacturing systems, autonomous vehicles, healthcare systems, medical informatics, etc. slow but steady progress on fundamental AI research problems continues. Synthesis of traditional logic-based systems, soft and adaptive computing technologies (e.g., neural networks, probabilistic models, etc.), crossdisciplinary work in cognitive sciences, and synthesis of software agents and multi-agent systems leads to the emergence of *nouvelle* AI which views intelligence as an emergent behavior resulting from interactions (e.g., communication, coordination, competition) among large numbers of autonomous or sem-autonomous entities (be they neurons, computer programs, individuals) that are situated in the world, display structure and organization at multiple spatial and temporal scales, and interact with the world through sensors and effectors; a host of fundamental problems such as design of individual agents, inter-agent communication and coordination, agent organizations, become topics of active research.

EXHIBIT 2

Symbolic Artificial Intelligence and Numeric Artificial Neural Networks: Towards A Resolution of Dichotomy

TR94-14

Vasant Honavar

August 18, 1994

Iowa State University of Science and Technology
Department of Computer Science
226 Atanasoff
Ames, IA 50011

12

SYMBOLIC ARTIFICIAL INTELLIGENCE AND NUMERIC ARTIFICIAL NEURAL NETWORKS: TOWARDS A RESOLUTION OF THE DICHOTOMY

Vasant Honavar

Department of Computer Science
Iowa State University
Ames, Iowa 50011

1 INTRODUCTION

The attempt to understand intelligence entails building theories and models of brains and minds, both natural as well as artificial. From the earliest writings of India and Greece, this has been a central problem in philosophy. The advent of the digital computer in the 1950's made this a central concern of computer scientists as well (Turing, 1950). The parallel development of the theory of computation (by John von Neumann, Alan Turing, Emil Post, Alonzo Church, Steven Kleene, Markov and others) provided a new set of tools with which to approach this problem — through analysis, design, and evaluation of computers and programs that exhibit aspects of intelligent behavior — such as the ability to recognize and classify patterns; to reason from premises to logical conclusions; and to learn from experience.

In their pursuit of artificial intelligence and mind/brain modelling, some wrote programs that they executed on serial stored-program computers (e.g., Newell, Shaw and Simon, 1963; Feigenbaum, 1963); Others had more parallel, brain-like networks of processors (reminiscent of today's connectionist networks) in mind and wrote more or less precise specifications of what such a realization of their programs might look like (e.g., Rashevsky, 1960; McCulloch and Pitts, 1943; Selfridge and Neisser, 1963; Uhr and Vossler, 1963); and a few took the middle ground (Uhr, 1973; Holland, 1975; Minsky, 1963; Arbib, 1972; Grossberg, 1982; Klir, 1985).

It is often suggested that two major approaches have emerged — symbolic artificial intelligence (SAI) and (numeric) artificial neural networks (NANN or connectionist networks) and some (Norman, 1986; Schneider, 1987) have even suggested that they are fundamentally and perhaps irreconcilably different. Indeed it is this apparent dichotomy between the two apparently disparate approaches to modelling cognition and engineering intelligent systems that is responsible for the current interest in computational architectures for integrating neural and symbolic processes. This topic is the focus of several recent books (Honavar and Uhr, 1994a; Goonatilake and Khebbal, 1994; Levine and Aparicioiv, 1994; Sun and Bookman, 1994). This raises some important questions: What exactly are symbolic processes? What do they have to do with SAI? What exactly are neural processes? What do they have to do with NANN? What (if anything) do SAI and NANN have in common? How (if at all) do they differ? What exactly are computational architectures? Do SAI and NANN paradigms need to be integrated? Assuming that the answer to the last question is yes, what are some possible ways one can go about designing computational architectures for this task? This chapter is an attempt to *explore* some of these fundamental questions in some detail.

This chapter argues that the dichotomy between SAI and NANN is more perceived than real. So our problems lie first in dispelling misinformed and wrong notions, and second (perhaps more difficult) in developing systems that take advantage of both paradigms to build useful theories and models of minds/brains on the one hand, and robust, versatile and adaptive intelligent systems on the other. The first of these problems is best addressed by a critical examination of the popular conceptions of SAI and NANN systems along with their philosophical and theoretical foundations as well as their practical implementations; and the second by a judicious theoretical and experimental exploration of the rich and interesting space of designs for intelligent systems that integrate concepts, constructs, techniques and technologies drawn from not only SAI (Ginsberg, 1993; Winston, 1992) and NANN (McClelland and Rumelhart, 1986; Kung, 1993; Haykin, 1994; Zeidenberg, 1989), but also other related paradigms such as statistical and syntactic pattern recognition (Duda and Hart, 1973; Fukunaga, 1990; Fu, 1982; Miclet, 1986)), control theory (Narendra and Annaswamy, 1989) systems theory (Klir, 1969), genetic algorithms (Holland, 1975; Goldberg, 1989; Michalewicz, 1992) and evolutionary programming (Koza, 1992). Exploration of such designs should cover a broad range of problems in perception, knowledge representation and inference, robotics, language, and learning, and ultimately, integrated systems that display what might be considered human-like general intelligence.

Knowledge Engineering

Knowledge engineering is a field within artificial intelligence that develops knowledge-based systems. Such systems are computer programs that contain large amounts of knowledge, rules and reasoning mechanisms to provide solutions to real-world problems.

A major form of knowledge-based system is an expert system, one designed to emulate the reasoning processes of an expert practitioner (i.e. one having performed in a professional role for very many years). Typical examples of expert systems include diagnosis of bacterial infections, advice on mineral exploration and assessment of electronic circuit designs.

Importance of Knowledge Acquisition

The early years of knowledge engineering were dogged by problems. Knowledge engineers found that acquiring enough high-quality knowledge to build a robust and useful system was a very long and expensive activity. As such, knowledge acquisition was identified as the bottleneck in building an expert system. This led to knowledge acquisition becoming a major research field within knowledge engineering.

The aim of knowledge acquisition is to develop methods and tools that make the arduous task of capturing and validating an expert's knowledge as efficient and effective as possible. Experts tend to be important and busy people; hence it is vital that the methods used minimise the time each expert spends off the job taking part in knowledge acquisition sessions.

Knowledge Engineering Principles

Since the mid-1980s, knowledge engineers have developed a number of principles, methods and tools that have considerably improved the process of knowledge acquisition. Some of the key principles are summarised as follows:

- Knowledge engineers acknowledge that there are different types of knowledge, and that the right approach and technique should be used for the knowledge required.
- Knowledge engineers acknowledge that there are different types of experts and expertise, such that methods should be chosen appropriately.
- Knowledge engineers recognise that there are different ways of representing knowledge, which can aid the acquisition, validation and re-use of knowledge.
- Knowledge engineers recognise that there are different ways of using knowledge, so that the acquisition process can be guided by the project aims.
- Knowledge engineers use structured methods to increase the efficiency of the acquisition process.

Knowledge Engineering Methodologies

Epistemics is involved in three methodologies to support the development of knowledge systems:

- CommonKADS
- SPEDE
- MOKA

Other Information:

- Knowledge Management
- Knowledge Acquisition
- Knowledge Modelling
- Glossary
- Quiz

Last modified: 20 November 2003 by Nick Milton